A Cross-Regional Collaborative, Privacy-Preserving, Generalized Federated Learning Quantitative Drug Detection Program in Point-of-Care Testing*

*Note: As the paper has not been published, only limited information is provided.

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Abstract

Artificial intelligence combined with Point-of-Care Testing greatly simplifies the inspection process and improves inspection accuracy. Although it is well known that high-quality AI models are built on a foundation of massive amounts of accessible data. However, the fragmentation of healthcare data and data silos, exacerbated by factors such as patient privacy, healthcare data security and legal constraints, are hindering the use of big data necessary to train AI models in clinical practice.

Here, to facilitate the aggregation of any medical image data from any data owner without violating privacy laws, we initiated A Cross-Regional Collaborative, Generalized Federated Learning Quantitative Drug Detection Program (CPGFD), which combines Federated Learning, Medical IoT, and Point-of-Care Testing. And we actually built a set of commercial landing applications of medical IoT (including multiple portable commercial fluorescence quantitative detection devices and parameter servers) based on cross-regional collaborative and federated transfer learning.

We select the most widely abused drug in the world today, heroin testing, to illustrate the feasibility of CPGFD's use of distributed data to develop quantitative drug assays. Using more than 2400 medical image data from different testing sites in 3 regions, we show that CPGFD's aggregated model for quantitative drug detection outperforms individual local models, taking into account the scarcity of medical data, model performance improvements, and strict requirements for privacy and security, and further evaluate the impact of multiple factors on the aggregated model.

In conclusion, our work advances the focus on privacy protection in healthcare and healthcare equity in resource-poor regions.

Keywords: Federal Learning, Privacy Protection, Point-of-Care Testing, Drug Detection, Medical IoT, Healthcare Equity

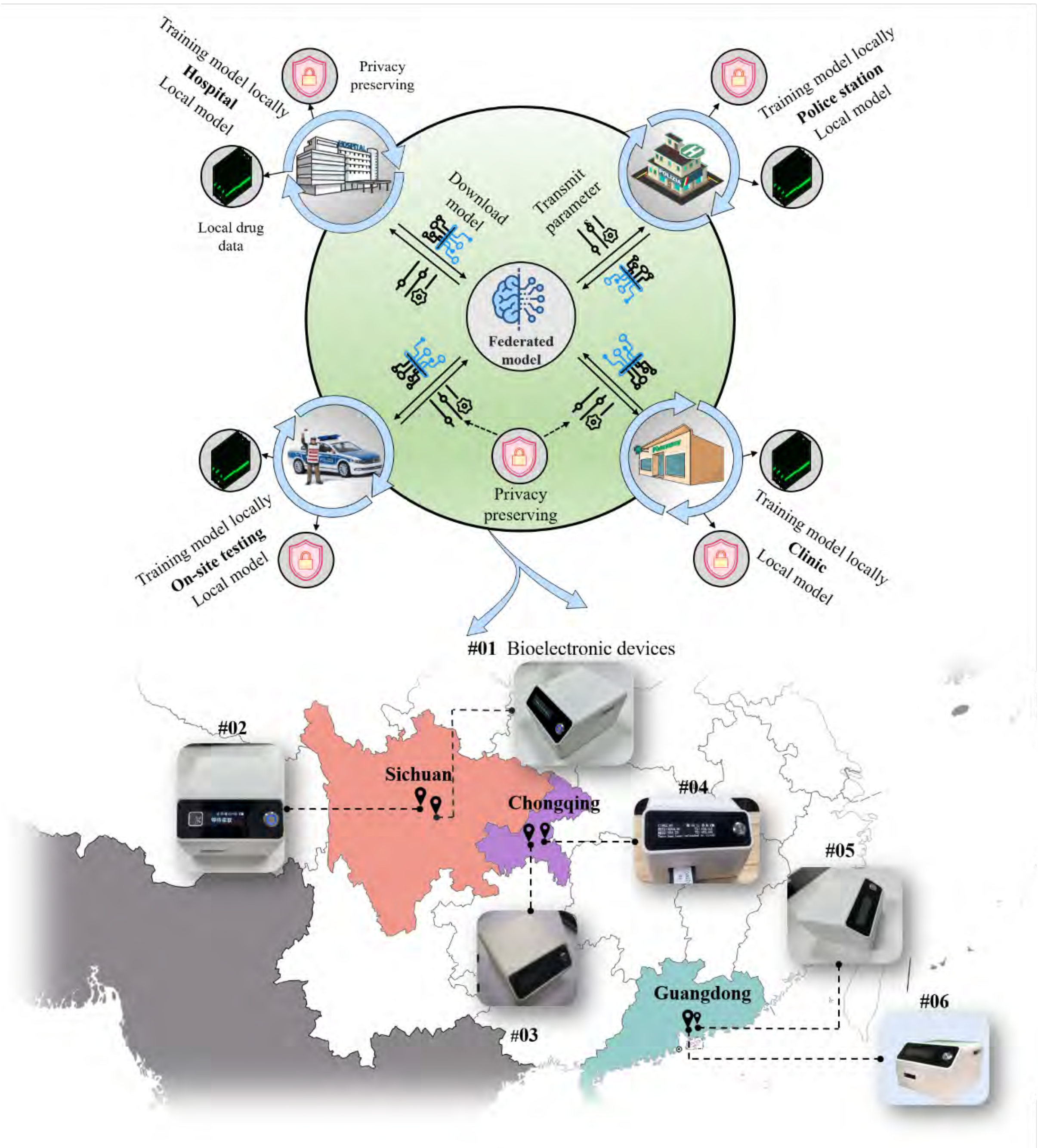

Figure 1: Example of client-server architecture for a quantitative drug detection model based on upconversion luminescence and artificial intelligence in a federal learning framework. The parameter server sends the initial model to each participant (testing devices in various institutions such as hospitals, clinics, police stations and field-testing sites in Chengdu, Chongqing and Shenzhen), and the participants train the model using their respective private datasets. The model parameters are updated and sent to the aggregation server in encrypted form. The aggregated model parameters are updated and sent back to the participants in encrypted form. This process will be repeated until the model converges, reaches the maximum number of iterations, or reaches the maximum training time (e.g., using algorithms such as FedAvg, Per-FadAvg, pFedMe, FedProx, FedFomo, MOCHA, FedAMP, and HeurFedAMP). Under this conceptual architecture, the original data of each participant is never exposed. This approach not only protects the privacy and data security of users. It also reduces the communication overhead associated with sending raw data. In addition, the aggregation server and the participants use encrypted forms (e.g., homomorphic encryption) to prevent model information leakage.

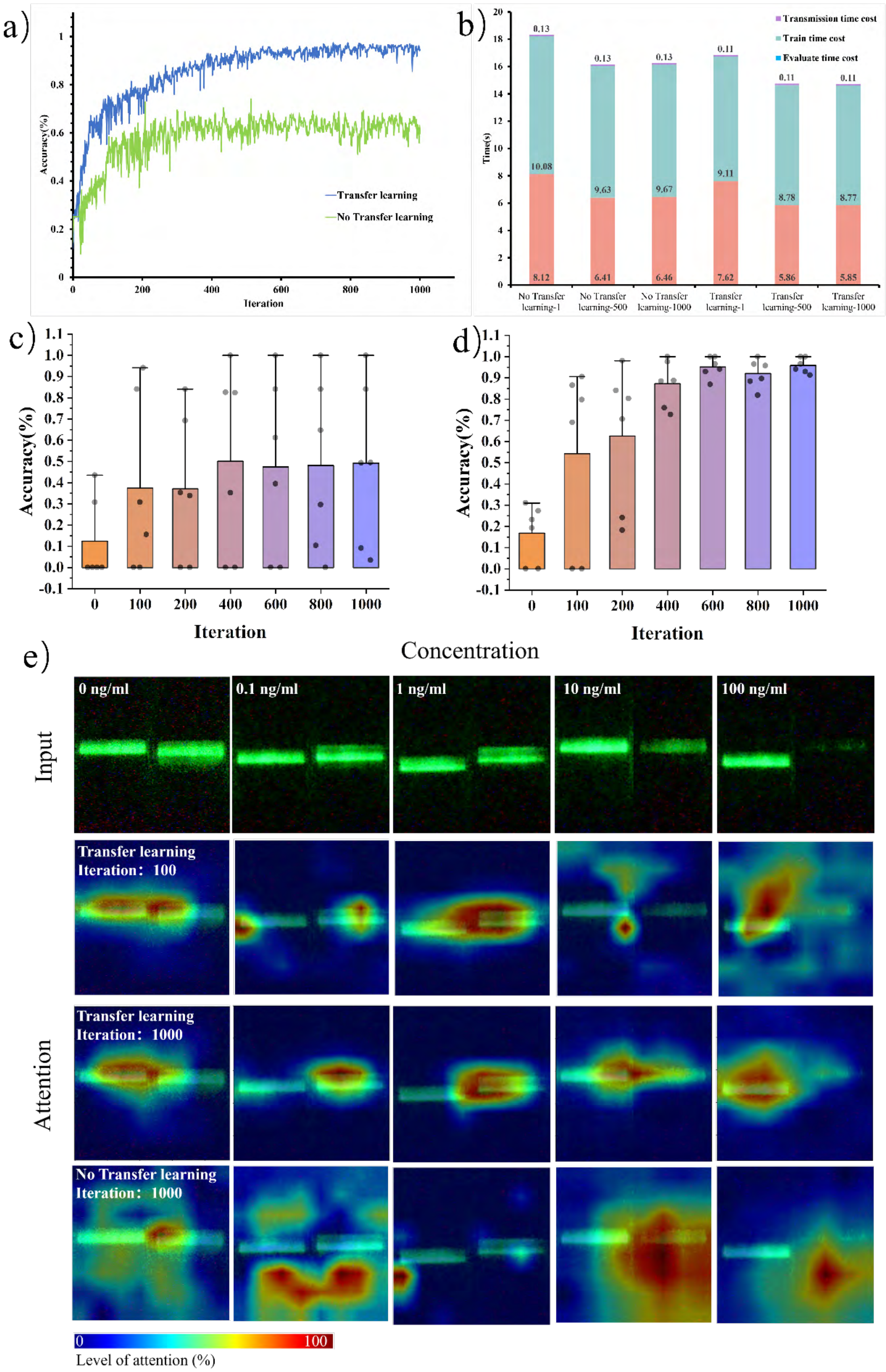

Figure 2: In the aggregation model, with and without using transfer learning in the model training process a) Accuracy comparison and b) Horizontal and vertical comparison of transmission time cost, train time cost and

evaluate time cost. c) Without using transfer learning and d) With using transfer learning, the impact of different number of iterations on the accuracy of the aggregation model and the accuracy of each distributed device. e) Use visualization to achieve interpretability of the aggregation model to help understand the aggregation model learning principles and guide the model to achieve higher accuracy.